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COMPARISON OF EIGHT DEMAND
FORECASTING MODELS

Robert J. Praggy Jr.
Second Lieutenant, USAF

LSSR 78-81

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This thesis studied eight forecasting models as a possible replacement for the model currently used at the Defense Electronics Supply Center (DESC). This model is a double exponential smoothing model with trend corrector and an α of 0.5. The models included in this study were: Naive, Maximum Likelihood, Polynomial Fitting, Moving Averages, and Exponential Smoothing. The results indicated that a single exponential smoothing model with an α of 0.3 may be the best model of those studied.

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COMPARISON OF EIGHT DEMAND FORECASTING MODELS

A Thesis

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the Requirement for the

Degree of Master of Science in Systems Management

By

Robert J. Praggy Jr., BS
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September 1981

This thesis, written by

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INTRODUCTION

Over the years demand forecasting has become an important function in many organizations. These forecasts are used to plan for production runs, inventory stockage levels, and manpower requirements in the future (2:230). Accurate forecasts enable an organization to make plans which are cost beneficial and in the best interest of the organization. Bad forecasts can result in high carrying costs for excess inventory, long delivery times due to a lack of items, and customer dissatisfaction because of unreliable suppliers to name a few examples.

This thesis was initiated by the Defense Electronic Supply Center's (DESC) desire to find a model which is "better" than the one currently in use. This is a double exponential smoothing model with a trend corrector (see Methodology for details). DESC is responsible for supplying electronic parts to all organizations within the Department of Defense. An accurate forecast of demand would enable DESC to order and stock items at a level which is optimal with respect to storage and purchase costs, and the ability to fill orders, demand, quickly. Also, the correct amount of stock ordered would reduce over- and under-stockage of items.

Demand Patterns

Demand follows four basic patterns which are also experienced in the private sector. These are:

1) Horizontal
2) Seasonal
3) Cyclic
4) Trend (12:8-11)

These demand patterns are the underlying factors when forecasting demand. Various models behave differently when demand has o : or all of these characteristic patterns.

A horizontal demand pattern exhibits no tendency to increase or decrease over time and demand in the next period has an equal change of increasing or decreasing (see Figure 1). Seasonal demand patterns are influenced by seasonal factors such as the time of the year. A product is consistently in demand during a certain part of the year every year. Products which follow this type of pattern are heating oil, ice cream, and soft drinks (see Figure 2) (12:9).

In a cyclic demand pattern, demand is influenced by longer-term economic fluctuations (12:9-10). It is different from a seasonal pattern in that a seasonal pattern is of a constant length and recurs on a regular, periodic basis. Cyclic patterns, however, vary both in length and magnitude. Products which follow this pattern include automobiles, steel, and major appliances (see Figure 3).

When demand follows a trend pattern, a long-term tendency to increase or decrease is present for that item (see

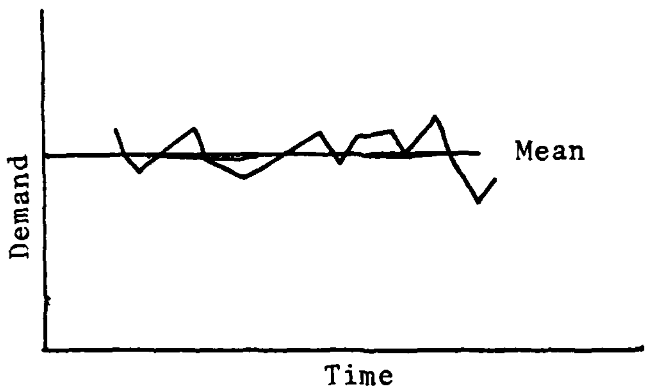

Figure 1

Horizontal Demand Pattern
(12:8)

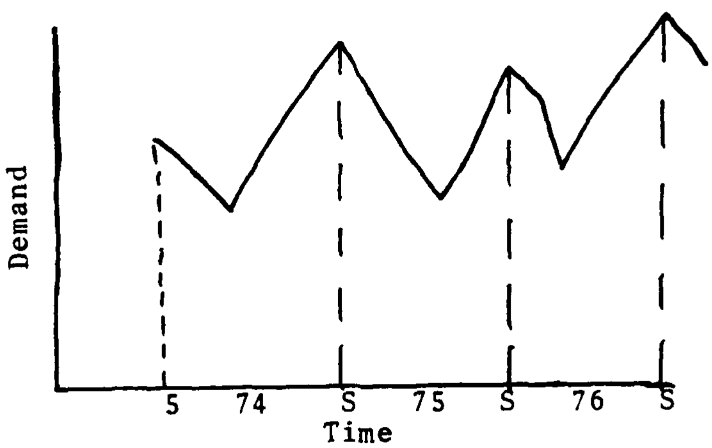

Figure 2

Seasonal Demand Pattern
(12:9)

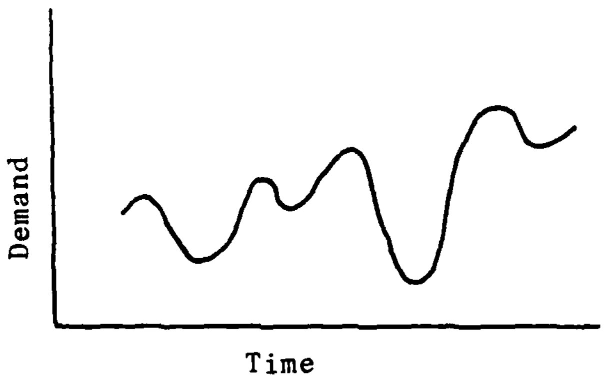

Figure 3

Cyclic Demand Pattern
(12:10)

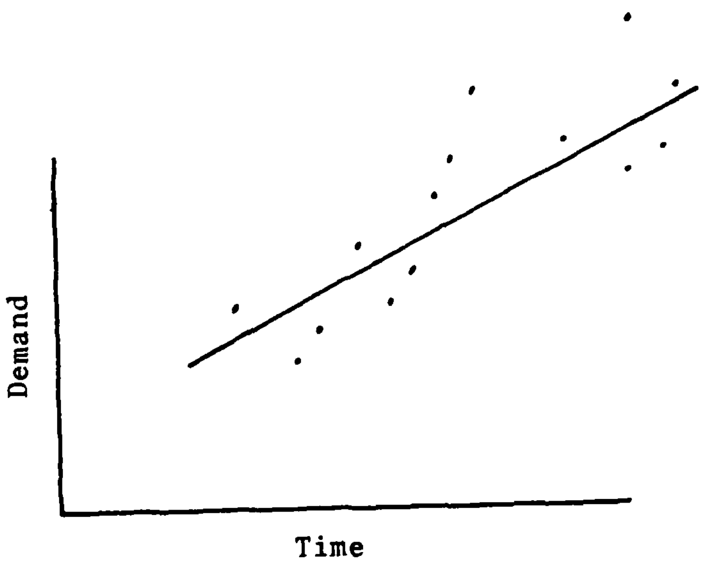

Figure 4

Trend Demand Pattern
(12:11)

Figure 4). Although these demand patterns are experienced in the private sector, DESC's items tend to follow the horizontal and trend patterns for all of their items.

The data used in this study consisted of replenishment and Numeric Stock Objective (NSO) items demand. Replenishment items are those which experience continuous demand from one quarter/period to the next. NSO items, however, experience very erratic and usually low demand. Demand is seldom, if ever, experienced two periods in a row for NSO items.

The purpose and aims of this study are summed up in the following sections.

Problem Statement

Can a "better" demand forecasting model be found to replace the double exponential model currently used at DESC?

Objective

The overall objective of this study is to compare selected forecasting models using two distinct types of data against DESC's model in an effort to find a model which minimizes forecast error.

Goals

The goals of this study are to:

1) Prepare two data bases where demand is continuous and erratic;

2) Computerize the models to be tested and obtain forecasts of demand using actual data obtained from DESC;

3) Compare the forecasts of the models using various statistics (Mean Absolute Deviation, for example);

4) Conduct an analysis of variance on the aforementioned quantities to see if any statistically significant differences are present.

In order to conduct this study, a literature review was performed. This enabled the author to see what has been done and how the various forecasting models behaved. From this review, the models used in this study were picked according to their effectiveness. The results of this review are contained in the next section.

Previous Research

Demand forecasting has been the subject of numerous studies over the years. This especially is true since the introduction of exponential smoothing by Robert Brown.

In 1968 the Defense Supply Agency compared exponential smoothing with other forecasting models then widely in use to show that exponential smoothing was better (3:1). This was due to resistance to double exponential smoothing when it was adopted by the Standard Automated Material Management System (SAMMS) to forecast demand. Three demand patterns were simulated:

1) A constant model with random fluctuations.

2) A theoretical ramp with steadily increasing demand. Three ramps were used; demand increased by 5%, 10%, and 20% with the initial demand equal to ten units.

3) A modified ramp which was based upon a DESC demand history of five months with a 10% ramp [3:2-3].

The criteria used to evaluate the forecasts were:

1) Total average absolute forecast error--measure accuracy

2) Number of items accurately forecasted by each method

3) Percentage of error to mean demand [3:3-4].

The study found that double exponential smoothing was slightly favorable over the other models used in the study (3:7).

Various single and double exponential smoothing models with differing smoothing constants, α, were studied along with a single and double moving average and moving least squares by Lum et al. (11:7-9). Demand patterns were generated by various combinations of mean demand, trends, and residual variance of demand from trend (11:31-31A). The models' forecasts were then evaluated using:

1) Mean Forecast Error (MFE) - measures bias in forecast method by computing an average;

2) Mean Absolute Forecast Error (MAFE) - measure variability of the forecast method; and

3) Root Mean Square Error (RMSFE) - measure variability using square roots (11:42, 44-46).

The MAFE was used to rank the models as to which was best, with the lowest value of the MAFE being the best forecast. These rankings were then compared against those obtained from the other two criteria for verification (11:47). They found that for Poisson probabilities, single moving average and

single exponential smoothing with $\alpha = 0.1$ gave the best forecasts (11:64). This was also the finding reached with non-trend items (11:65). With trends, double moving average, double exponential smoothing, and moving least squares gave the best results (11:66-69).

A thesis by Fischer and Gibson studying the forecasting of EOQ items found that there was no statistically significant differences between single and double exponential smoothing and moving average by conducting an analysis of variance on the Mean Forecast Error (4:49). However, double exponential smoothing showed a stronger negative bias than that of the moving average. This means that it more severely underestimates demand (4:50).

Zehna (1972) compared exponential smoothing with maximum liklihood and a Bayes model. He concluded that exponential smoothing gives better results when the variance is low but is still inferior to maximum liklihood (17:18). He also found that the Bayes model was well suited when mean demand was constant in a given period, but that more study was needed to see if Bayes is truely better (17:33).

Gross and Craig (1972) also studied maximum liklihood, exponential smoothing, and a Bayes forecasting model using Monte Carlo simulation. They assumed a Poisson demand with mean unknown in a given period (8:1). Three types of means were studied:

1) Stationary or constant

2) Long-term increasing trend

3) "Shock" changes at random times

Their comparison criterion was the sum of total discounted costs associated with the items. They concluded that:

1) In the long run when demand is not constant, exponential smoothing showed superior performance

2) When demand is constant, exponential smoothing performed poorer than the other models, but not significantly

3) When demand is unknown, exponential smoothing is preferred

4) When demand is constant and low, maximum liklihood is preferred

5) With no prior data, Bayes has some advantages in the initial periods [8:30-31].

Zehna and Taylor (1975) compared exponential smoothing with $\alpha = 0.1$ and 0.2 (S1 and S2 respectively), maximum liklihood (ML), and moving average (MA) (18:26). Five demand patterns were simulated:

1) Mean demand increases 50% in period 3 and then remains at that level

2) Mean demand increases 100% in period 3 and then remains at that level

3) Demand has an impulse; in period 3 mean demand increases 100% and then immediately decreases to its previous level where it remains

4) A theoretical ramp where the mean demand increases 10% in each period starting in period 3

5) A modified ramp where mean demand increases 10% in periods 3 & 4, and then remains constant [28:20].

The models were compared using the Mean Square Forecast Error for "it has an appeal as a measure of closeness and is functionally related to the variance [18:22]." They found that

patterns emerged according to the variance to mean ratios:

1) $\frac{\sigma^2}{\mu} \leq 1$; the models were ranked best to worst S2, MA, S1, ML except for pattern 3 where the order was ML, S1, S2, MA

2) $\frac{\sigma^2}{\mu} > 1$; pattern 4 order was S2, MA, S1, ML pattern 3 & 5 was ML, S1, S2, MA [18:27]

The authors then tested the models using real data obtained from the Ships Parts Control Center (18:28). Using the Mean Square Forecast Error for comparison, they found results similar to those obtained from the simulation (18:33-34). Maximum liklihood performed slightly better than exponential smoothing with $\alpha = 0.1$.

Looking at past research dealing with demand forecasting, it can be seen that a large amount of study has been devoted to theoretical and simulated data. In this study, actual demand data will be used to get a better indication of how selected forecasting models work with DESC demand patterns.

To summarize briefly, the aims of this study have been presented. Also, previous research in the area of demand forecasting has been looked at for the intent of selecting appropriate models for inclusion in this thesis. Chapter 2 will present the methodology employed in this study and will discuss the data base, the models used in this study, and the evaluation criteria. Chapter 3 will present the analysis of these forecasting models. Lastly, Chapter 4 will present the conclusions and recommendations of this study.

CHAPTER 2

METHODOLOGY

The overall process in this thesis consisted of exploring the literature to find what had been done in the area of demand forecasting, and selecting and testing appropriate models using actual demand data. The specific methodology employed was:

1) Obtain actual demand data from DESC;
2) Select and computerize the models picked;
3) Use the actual demand data to generate demand forecasts from the various models; and
4) Compare the forecasted demands against actual demand to find a "best" model.

Data

Twelve quarters of demand data were provided by the Operations Research, Analysis, and Projects Division at DESC. Appendix A shows the program used to compile the data. Two separate data bases were developed based upon the types of items DESC stocks and the nature of the demand these items experienced. These are:

1) Replenishment Items - demand is continuous and is experienced every quarter; and
2) Numeric Stock Objective Items (NSO) - demand is

sporadic and uncertain, and is not experienced every quarter.

Item migration, where the demand on an item moves from one category to another, is present in the universal data and must be taken into account when compiling the data bases. For this study, the data bases were constructed such that an item's demand remains in the same category for the entire twelve quarters. This causes an increase in the time required to select items for inclusion in this research.

A sample size of approximately 10,000 items for each base was picked using convenience sampling (9:196). This method is similar to the purposive quota sampling method employed by Garland and Mitchell (1980) in their study of the D062 Model versus Multiple Model Demand forecasting (5:20). This sampling method is non-probabilistic and states that items are selected for researcher convenience. This sampling method was selected and employed because the items had to fit the constraint of item migration, the large number of items in each category (300,000 and 100,000 respectively), and a forecasting model should give similar results for the same type of demand pattern (a large sample size is not needed). The models selected for use in this thesis will be discussed in the next section.

Models

Demand forecasting models exist in many forms from the simple to the complex. In selecting a forecasting model,

one must consider the strengths, weaknesses, and peculiar characteristics of those models to insure that appropriate models are used for the specific guidelines/patterns in the study. The following forecasting models will be used in this thesis and will be explained in greater detail:

1) Naive
2) Maximum Liklihood
3) Polynomial Fitting
4) Single Moving Average
5) Double Moving Average
6) Single Exponential Smoothing
7) Double Exponential Smoothing
8) AFLC D062 System

Naive. The naive model forecasts demand for the following period by using the most recent actual demand experienced (15:37). This model is used to get a rough forecast for use in comparison with other more sophisticated models.

$$F_{t+1} = D_t \tag{1}$$

where:

F_{t+1} = forecasted demand
D_t = demand of present period

Maximum Liklihood. Maximum liklihood is the arithmetic mean of all past demand observations. Thus, its forecasted demand is the mean of the actual demand up to the most recent period (8:3).

$$F_{ML} = \frac{\sum_{t=1}^{n} D_t}{n} \qquad (2)$$

where:

F_{ML} = forecasted demand

n = the number of periods

Polynomial Fitting. In polynomial fitting, N + 1 recent observations are fitted into an Nth order polynomial (15:84). The forecasted demand is then an extension of the polynomial curve. Using the method of first differences, a polynomial curve can be fitted to three observations (15:84):

$$F_{t+1} = 3D_t - 3D_{t-1} + D_{t-2} \qquad (3)$$

where:

F = the forecasted demand

D = the actual demand

A shortcoming of this method is that random fluctuations and noise are ignored and, therefore, may be present in the fitted curve.

Single Moving Average. A moving average forecasts demand in a manner similar to maximum liklihood; the only difference being that a moving average uses a predetermined amount or number of past demand points (2:232). Moving averages are employed to "smooth" historical demand observations and eliminate randomness. A four-quarter single moving average is:

$$F_{t+1} = \frac{D_t + D_{t-1} + D_{t-2} + D_{t-3}}{4} \qquad (4)$$

where F and D are forecasted and actual demand respectively.

A weighted moving average assumes that the latest demand experienced is more indicative of the next period's demand and is "weighted" accordingly (2:233). This offsets some of the inability of a single moving average to adapt and respond quickly to changes in the demand pattern (15:60). A four-quarter model will be used with the weights shown in Table 1. These weights were selected to see what difference in the forecast is made if the weights are gradual (Set I) and abrupt (Set II).

TABLE 1

Single Moving Average Weights

	Set I	Set II
W_t	4	4
W_{t-1}	3	1
W_{t-2}	2	1
W_{t-3}	1	1

The demand forecasts are made according to Eqs. 5 and 6.

$$F_{t+1} = \frac{4D_t + 3D_{t-1} + 2D_{t-2} + D_{t-3}}{10} \quad (5)$$

$$F_{t+1} = \frac{4D_t + D_{t-1} + D_{t-2} + D_{t-3}}{7} \quad (6)$$

where F and D are forecasted and actual demand respectively.

Double Moving Average. A double moving average operates in the same way as a single moving average. It takes a

moving average based upon a single moving average (15:67). To arrive at a forecast, the difference between the Nth single moving average and the Nth double moving average is added to the single moving average (see Eq 8). An adjustment factor is then calculated and added to the above figure to get a forecast. This technique enables the moving average to respond better to trends, be more accurate, and overcome some of the drawbacks of a single moving average. The equations for a four-quarter model are:

$$F''_t = \frac{F_t + F_{t-1} + F_{t-2} + F_{t-3}}{4} \tag{7}$$

$$a_t = 2F_t - F''_t \tag{8}$$

$$b_t = (2/3)(F_t - F''_t) \tag{9}$$

$$E_t = a_t + b_t \tag{10}$$

where:

F_t = the single moving average forecast for period t

F''_t = the double moving average forecast for period t

a_t = the rough forecast for period t

b_t = the adjustment factor where 2 is a constant and 3 is the number of quarters in the moving average, 4, minus 1

E_t = the actual forecast for period t

A disadvantage of this model, however, is that it requires a large data base and number of calculations to make its forecast (15:72).

<u>Exponential Smoothing</u>. Exponential smoothing operates

on the premise that the most recent demands experienced are more indicative of the future than are old demands (2:234). This is the same as moving average except in the weighting of the observed demands. Whereas moving average weighs N observations for an N quarter, period, model; exponential smoothing weighs all past demands to some extent for an N quarter model with a smoothing constant, α (15:62). This smoothing constant produces an "average in which past observations are geometrically discounted according to their age [1:106]." α is selected on the basis of how responsive the model has to be. Small values of α tend to maximize the smoothing of random fluctuations while large values improve the rate of response to a changing pattern (1:107). Also, exponential smoothing requires less storage space and data for forecasting calculations. There will be three exponential smoothing models: single without a trend corrector; single with a trend corrector; and double with trend corrector (DESC model).

The single exponential smoothing model without trend corrector is calculated by the following equation:

$$S_{t+1} = \alpha(D_t - S_t) + S_t \qquad (11)$$

where:

S_{t+1} = the single forecasted demand for the next period

α = the smoothing constant

D_t = the present period's demand

S_t = the single forecasted demand for the present period

This model, like single moving average with equal weights, is limited when the demand pattern changes. It reacts better to horizontal demand patterns (15:65). To overcome this, a trend corrector has been developed along with double exponential smoothing.

With a trend corrector, single exponential smoothing can react better to trends and other changes in the demand pattern. Eq. 11 is modified to include a trend corrector, T.

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1} \qquad (12)$$

$$S_{t+1} = \alpha D_t + (1 - \alpha)(S_t + T_t) \qquad (13)$$

where:

T_t = the trend corrector

β = the smoothing constant for the trend corrector and is equal to 0.5 (10)

β is similar to α in its operation and has the same characteristics.

As previously mentioned, DESC currently uses a double exponential smoothing model with a trend corrector. The model uses an α value of 0.5 and develops a forecast based upon the computation of a single smoothed, S_t, and a double smoothed, S''_t, forecast of an item's demand (13:5-6). Using Eq. 11 for the value of S_t, the demand is forecasted according to Eqs. 14 and 15:

$$S''_t = \alpha(S_{t+1} - S''_t) + S''_t \qquad (14)$$

$$ED_t = 2S_{t+1} - S''_{t+1} \qquad (15)$$

where:

S''_{t+1} = the new double forecasted demand

S''_t = the present period's double forecasted demand

S_{t+1} = the new single forecasted demand

α = the smoothing constant

ED_t = the new forecasted demand for the upcoming period

Double exponential smoothing responds better to trends and other demand complexities than single smoothing.

For each of these smoothing models, α will be varied from 0.1 to 0.9 to assess its impact upon the forecast results and find those values of α which are best for each model. Also, use of exponential smoothing requires a forecasted demand quantity before it begins. To satisfy this, an approximation must be used. For the single models, 75 percent of the first quarter's demand will be used for S_t, and 85 percent will be used for the double model, S''_t.

AFLC DO62 System. Air Force Logistics Command currently uses an eight-quarter moving average to forecast demand (14:1-2). This model uses seven full quarters of data plus the cumulative data of the present quarter in its forecast calculations (14:7-1). Quarter eight demand is approximated by computing the fraction of the quarter already passed. The system then computes a Monthly Demand Rate (MDR) (14:7-1):

$$\text{fraction} = \frac{\text{days in quarter}}{91} \tag{16}$$

$$\text{MDR} = \frac{\text{DUC(curr quart + total quart)}}{\text{3(quart tally + curr quart)}} \tag{17}$$

where:

DUC is the demand for each quarter

Curr quart is the present quarter

Total quart and quart tally are the last seven quarters.

For an eight-quarter moving average without approximating quarter 8, Eq. 17 can be modified and rewritten:

$$MDR = \frac{D_t + D_{t-1} + D_{t-2} + \dots + D_{t-7}}{3(8)} \qquad (18)$$

where:

8 = the number of quarters

3 = the conversion factor for a monthly forecast

The forecast for a quarter is then obtained by:

$$\text{Quarter forecast} = 3 \times MDR \qquad (19)$$

Eqs 18 and 19 will be used in this thesis since full quarters of data are available. The next step after selecting the models is to decide on how those models selected are to be evaluated.

Statistical Methods

In using forecasting models, it is important to be able to evaluate the performance of these models. Accuracy in a model is essential. The statistic used for this is the forecast error.

In this study, the accuracy of the forecasting models was measured using the Mean Absolute Deviation (MAD) and the Mean Forecast Error (MFE). In general, the lower the value of the MAD, the better the accuracy of the model. This is also

true of the MFE. Accuracy is defined here as the closeness of the forecasted demand to the actual demand. The MAD measures the average magnitude of the forecast error. It can be calculated as follows:

$$\mathrm{MAD} = \frac{\sum_{t=1}^{n} |D_t - F_t|}{n} \tag{20}$$

where:

D_t = the actual demand for period t

F_t = the forecasted demand for period t

n = the total number of periods computed in the study

The mean forecast error is different from the MAD in that it considers the magnitude and direction of the error (4:26). It can be calculated as follows:

$$\mathrm{MFE} = \frac{\sum_{t=1}^{n} (D_t - F_t)}{n} \tag{21}$$

where all items are the same as in the MAD computations. In general, a positive MFE means the forecast model over-estimated demand and a negative demand means the forecast model under-estimated demand.

Another point of interest in the analysis of forecasting models is the variance of the forecasts. The variance gives the range over which a forecast's result could vary. A high variance indicates that the model is unstable, while a low variance means that the model is stable. Ideally, a variance of zero is desirable to make the forecasting model exact.

The variance of a model is very important in a model's results, for if the forecast has a large variance and a low MAD or MFE, the forecast is no good since it has large fluctuations present (18:2). The variance can be computed by the following equation:

$$VAR = \frac{\sum_{t=1}^{n} (D_t - F_t)^2}{n} \tag{22}$$

where VAR is the variance.

Summary

The forecasting models included in this study were selected because they are able to handle the types of demand patterns apt to be found in the sample data--namely, trends and horizontal demand patterns. In the next chapter, the forecasts obtained from these models will be compared according to the test statistics mentioned in this chapter.

CHAPTER 3

RESULTS AND ANALYSIS

The analysis of results will be divided into three parts. The first part will be the analysis of the replenishment item base; the second will be the analysis of the NSO item base; and the third will be an analysis of how well DESC's model worked in relation to the other models. The model abbreviations used in the succeeding chapters are defined in Table 2.

TABLE 2

Model Definitions

SESα.a	=	single exponential smoothing with α of 0.a
SETα.a	=	single exponential with trend and α of 0.a
DESα.a	=	double exponential smoothing with α of 0.a
MXLK	=	maximum likelihood
NAV	=	naive
SMA	=	single moving average
DMA	=	double moving average
ETMA	=	DO62 model
PF	=	polynomial fitting
WMASc	=	weighted moving average set c

Replenishment Item Base

There was a total of 13,074 items in the replenishment

data base. The forecasts' statistics are located in Tables 3 through 6. These tables are arranged in the order of increasing Mean Average Deviation (MAD), with the lowest MAD being the "best" model. The Mean Forecast Error (MFE) is a running sum of the difference between the actual and forecasted demand. A positive value indicates that the forecast model has a tendency to underforecast demand, while a negative value indicates overforecasting. The variance (VAR) is the limit of the value's range where a model's forecast will probably fall. The forecasted demands are located in Table 10 in Appendix C. This table shows the actual and forecasted demand for each of the twelve quarters of data covered in this study.

Using the aggregate statistics in Table 3, the best model appears to be a single exponential model with an α of 0.3 and a MAD of 45.10. This means that this model has the lowest deviation from the actual demand. There are a number of models close to SESα.3 in their MAD value which have a lower MFE and/or a smaller variance. These are maximum likelihood, single moving average, and SESα.4 (see Table 7). Thus, any one of these models could be the "best." The MFE's indicate that these other models will have lower deviance in the long run. The small variance of the SMA model means that it is closest to the actual demand pattern in range. To get an idea of how well the forecasts match the actual demand, results from the top models were graphed against the demand pattern (see Figures 5 and 6).

As seen in the graphs, the models are roughly alike

TABLE 3

Aggregate Replenishment Statistics

Model	MAD	MFE	VAR
SESα.3	45.10	7.45	180568.31
SESα.2	45.18	10.66	179397.75
SESα.4	45.44	5.51	186152.94
MXLK	45.92	2.84	186653.44
SESα.5	46.01	4.26	194705.50
SMA	46.03	2.30	154637.38
WMAS1	46.20	2.12	158407.88
SESα.1	46.54	16.29	187552.50
SESα.6	46.80	3.38	205765.63
WMAS2	46.81	2.29	166500.94
SETα.1	47.67	8.42	192984.31
SESα.7	47.77	2.75	219236.19
SETα.4	48.20	2.39	199851.38
SETα.3	48.24	2.58	195617.00
SETα.2	48.25	3.60	194124.81
SETα.5	48.31	2.22	206116.81
SETα.6	48.61	1.88	214526.56
SESα.8	48.89	2.30	235252.38
ETMA	49.01	8.13	218937.25
SETα.7	49.07	1.72	225335.44
SETα.8	49.70	1.70	238830.31
DESα.1	49.92	18.21	208478.00
SESα.9	50.24	1.96	254151.25
SETα.9	50.58	1.69	255523.75
NAV	69.83	4.19	356069.69
DMA	88.77	53.75	459991.13
DESα.2	97.22	32.83	400661.00
DESα.3	143.00	43.84	583577.69
PF	171.02	0.91	2833057.00
DESα.4	188.37	52.11	763265.25
DESα.5	233.67	58.46	943909.44
DESα.6	279.21	63.40	1129775.00
DESα.7	325.38	67.31	1325710.00
DESα.8	372.68	70.44	1537990.00
DESα.9	421.73	72.99	1775504.00

TABLE 4

High Replenishment Statistics

Model	MAD	MFE	VAR
SMA	459.23	13.81	2359768.00
WMAS1	463.35	14.62	2449381.00
SESα.3	463.81	54.64	2860499.00
SESα.4	465.16	38.00	2966021.00
SESα.2	467.81	83.22	2821556.00
SESα.5	469.88	27.48	3115684.00
WMAS2	471.27	18.29	2581176.00
MXLK	471.44	-12.54	2909737.00
SESα.6	477.78	20.42	3302946.00
SESα.7	487.86	15.49	3526960.00
SESα.1	488.23	136.35	2929694.00
SETα.4	492.91	7.55	3197721.00
SETα.5	493.27	7.13	3307159.00
SETα.3	495.27	5.49	3117846.00
SETα.6	496.42	5.94	3449202.00
SETα.1	497.51	38.84	3029154.00
ETMA	498.63	90.93	3320175.00
SETα.2	498.63	4.65	3077176.00
SESα.8	499.78	11.96	3790407.00
SETα.7	501.29	5.59	3628625.00
SETα.8	507.87	6.05	3850325.00
SESα.9	513.87	9.39	4098954.00
SETα.9	517.26	6.80	4122370.00
DESα.1	527.49	133.92	3246111.00
NAV	531.92	6.89	4462095.00
DMA	965.97	-671.01	7439216.00
DESα.2	1022.81	237.89	6234942.00
DESα.3	1499.13	312.37	9094343.00
PF	1730.69	5.19	45465984.00
DESα.4	1966.99	365.35	11918031.00
DESα.5	2431.63	403.52	14776065.00
DESα.6	2897.49	431.12	17735600.00
DESα.7	3368.85	451.07	20872032.00
DESα.8	3852.04	465.54	24283584.00
DESα.9	4353.70	476.21	28110464.00

TABLE 5

Medium Replenishment Statistics

Model	MAD	MFE	VAR
SESα.2	41.27	7.99	25270.40
SESα.3	41.36	5.59	26234.85
SESα.4	41.86	4.11	27525.82
MXLK	42.16	2.52	24966.61
SESα.1	42.21	12.36	25056.02
ETMA	42.46	2.83	14507.49
SESα.5	42.51	3.16	29054.55
SMA	42.74	1.55	33245.66
WMAS1	42.78	1.52	34255.59
SETα.1	42.90	7.96	25966.04
WMAS2	43.29	1.50	36146.28
SESα.6	43.29	2.54	30843.82
SETα.2	43.99	3.29	27843.21
SESα.7	44.20	2.08	32932.02
SETα.3	44.29	1.99	29238.41
SETα.4	44.47	1.81	30352.68
SETα.5	44.65	1.77	31427.87
SETα.6	44.94	1.48	32668.65
SESα.8	45.25	1.74	35382.86
SETα.7	45.41	1.37	34193.77
DESα.1	45.70	14.53	26165.93
SETα.8	46.01	1.35	36103.23
SESα.9	46.52	1.47	38289.25
SETα.9	46.83	1.28	38542.71
NAV	48.14	0.79	41774.22
DMA	73.53	-39.89	71201.25
DESα.2	88.93	25.92	51402.14
DESα.3	130.94	34.52	76533.81
PF	158.12	1.15	458965.56
DESα.4	172.59	40.90	102136.69
DESα.5	214.30	45.78	128565.94
DESα.6	256.35	49.68	156229.13
DESα.7	299.07	52.81	185595.38
DESα.8	342.81	55.35	217469.13
DESα.9	388.17	57.43	253179.19

TABLE 6

Low Replenishment Statistics

Model	MAD	MFE	VAR
SESα.1	11.60	7.86	22340.95
SESα.2	11.66	5.69	19278.60
SESα.3	11.83	4.26	17396.86
DESα.1	11.96	10.05	26332.73
SESα.4	12.04	3.36	16335.07
MXLK	12.11	4.24	22710.74
SETα.1	12.21	6.08	21702.70
SESα.5	12.23	2.76	15870.54
SESα.6	12.43	2.29	15863.15
SETα.2	12.56	3.63	18674.28
SESα.7	12.66	1.96	16224.75
SETα.3	12.71	2.57	16956.26
SETα.4	12.78	2.19	16111.00
SETα.5	12.84	1.98	15805.57
SETα.6	12.91	1.69	15874.44
SESα.8	12.92	1.72	16907.82
WMAS1	12.93	1.32	15957.87
WMAS2	12.97	1.27	16164.63
SETα.7	13.00	1.54	16247.96
SMA	13.04	1.63	18250.53
SETα.8	13.14	1.47	16905.75
SESα.9	13.25	1.53	17899.34
SETα.9	13.35	1.42	17871.71
NAV	13.72	0.93	19215.14
DMA	21.90	-7.88	29961.64
DESα.2	23.75	18.49	50468.96
DESα.3	35.51	25.15	72200.13
PF	47.03	0.46	206237.81
DESα.4	47.34	30.43	91630.31
DESα.5	59.51	34.70	109210.00
DESα.6	71.40	38.16	125551.44
DESα.7	83.67	41.04	141335.19
DESα.8	96.21	43.46	157292.25
DESα.9	109.15	45.51	174296.25

TABLE 7

Model Summary

Model	MAD	MFE	VAR
SESα.3	45.10	7.45	180568.31
SESα.4	45.44	5.51	186152.94
MXLK	45.92	2.84	186653.44
SMA	46.03	2.30	154637.38

in their forecasts after the fifth period. They show a horizontal-type pattern with a slight upturn after the abrupt peak. The averaging techniques were fairly close together in their forecast patterns (see Figure 6) and tended to cut through the middle of the actual demand pattern. The exponential smoothing models lagged below the actual demand for the first five periods. This lag is primarily attributed to the initial value selected for the model. After period 5, the model follows the actual demand patterns closely except for the abrupt peak in period 9.

With Tables 4 through 6, additional information on the merits of these models can be found by seeing how they rank in the components of the aggregate demand (high, medium and low demand). An item was classified as low if it experienced less than 20 units demanded in quarter 1; medium if less than 200; and high if greater than 200. For a model high on the aggregate scale, it should rank relatively high on all of the component tables if it is indeed a "best" model. Using the same criteria as that on Table 3, single exponential smoothing with an α of 0.3 and 0.4, and maximum

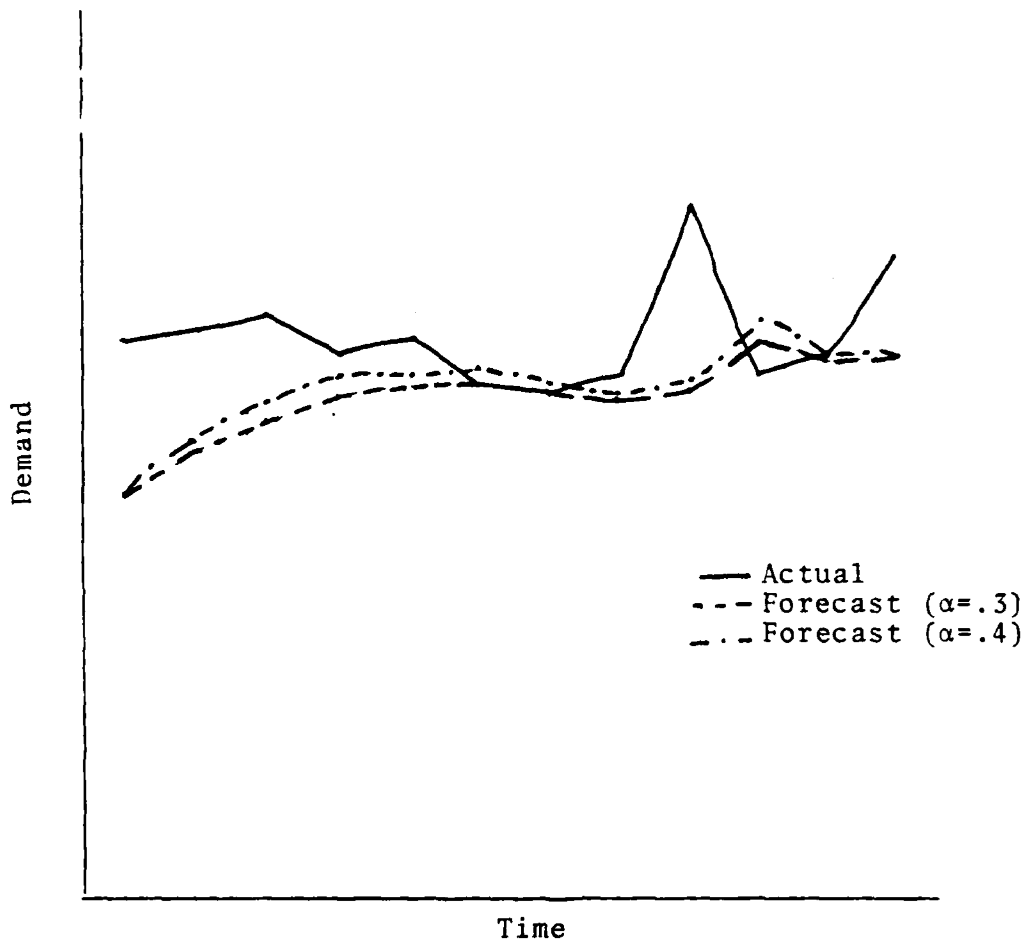

Figure 5

Single Exponential Smoothing

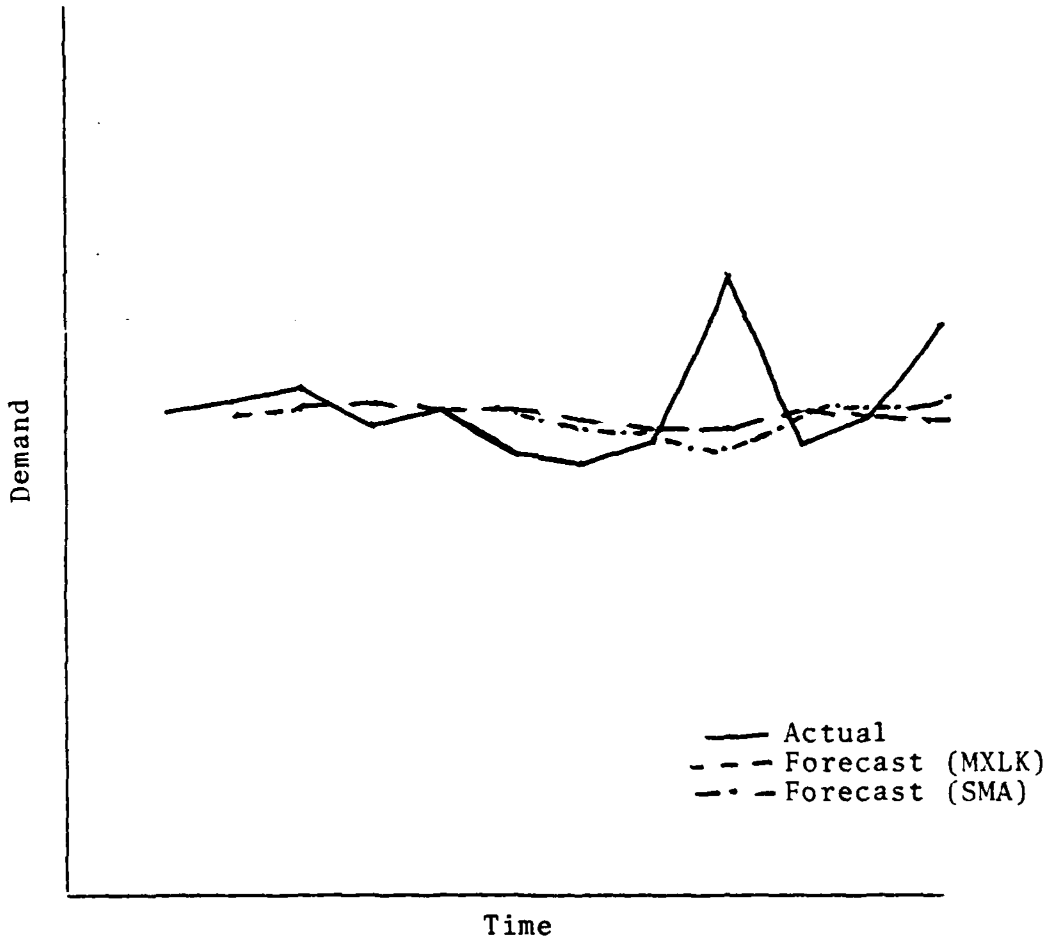

Figure 6

Averaging Methods

likelihood are within the top eight on all three tables. SESα.3 is also within the top three models on all three tables with MADs of 463.81, 41.36, and 11.83. This indicates that SESα.3 is a very able predictor of DESC-experienced demand. The single moving average model performed well on the high and medium tables, but only average on the low one. The maximum likelihood model still led with the lowest MFEs: -12.54, 2.52, and 4.24.

Figure 7 illustrates the demand patterns for each of the components and how well the SESα.3 and MXLK model forecasts follow them. The demand patterns obtained from the average demand per item in each category reflect either a horizontal or trend pattern. This is consistent with the exclusion of migratory items from the data base. The trend pattern in the high demand category reflects the large size of this category. The low and medium demand patterns are fairly stable, and both models' forecasts follow these patterns closely. The high demand pattern appears to follow a more erratic path. The maximum likelihood model tends to stay on a horizontal-type pattern. This causes it to overforecast demand throughout most of the pattern. Thus, this explains the negative MFE obtained from Table 4. The single exponential model attempts to follow the demand pattern in its erratic course, but lags behind the pattern for the most part.

Numeric Stock Objective Item Base

There was a total of 9593 NSO items in the data base.

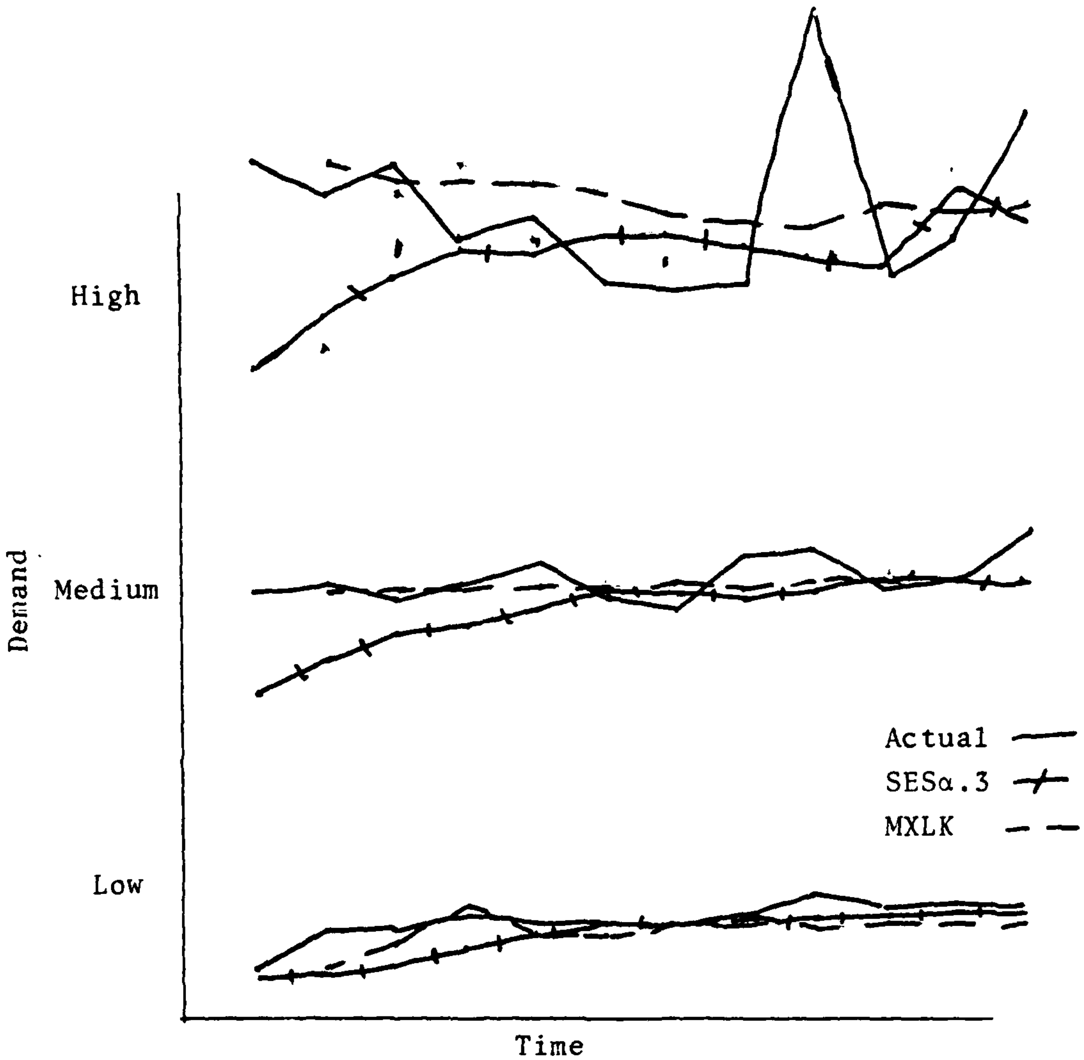

Figure 7

Replenishment Component Demand Patterns

The forecast statistics are presented in Table 8, and the forecasted demands are in Table 11, Appendix C.

Since NSO items experience low demands, when they have demand, the models which work best should be similar to those models which ranked high on low replenishment item demands (Table 6). Analyzing Table 8, this seems a valid assumption. This table indicates that a single exponential smoothing model with α = 0.2 is the "best" model. However, SESα.3 and MXLK rank just behind and both have a lower MFE and variance, and may, therefore, be a better model.

Table 9 shows a quick comparison of these three models. In fact, Table 8 indicates that for NSO items, single exponential smoothing with any value of α is better than moving averages or double exponential smoothing. Table 9 MFEs show that in the long run, MXLK and SESα.3 has virtually no deviation from the actual demand. Figure 8 illustrates the NSO demand pattern with maximum likelihood, and single exponential smoothing with α of 0.2 and 0.3. The demand pattern follows a horizontal pattern with peaks every four periods either up or down. The forecasting models tend to settle into a straight line. Thus, in the long run, any one of these graphed models would serve as a reasonable forecaster.

DESC's Model

DESC's double exponential smoothing model with an α of 0.5 did not fare well in the MAD rankings. On the replenishment items it had a MAD of 233.67 compared with 45.10 for

TABLE 8

NSO Statistics

Model	MAD	MFE	VAR
SESα.2	2.80	2.47	851.56
MXLK	2.81	0.99	808.22
SETα.1	2.82	1.03	935.66
SESα.3	2.82	0.85	778.70
SESα.1	2.83	1.21	1068.73
SESα.4	2.86	0.70	757.53
SESα.5	2.91	0.60	760.52
SESα.6	2.96	0.48	779.15
SETα.2	2.96	1.01	896.88
DESα.1	2.99	1.23	1675.60
SESα.7	3.01	0.41	811.04
SETα.3	3.02	0.74	855.82
SESα.8	3.05	0.37	855.75
SETα.4	3.05	0.60	831.29
SETα.5	3.07	0.52	820.42
SETα.6	3.10	0.40	821.83
SESα.9	3.10	0.33	914.63
SETα.7	3.11	0.34	837.33
SETα.8	3.12	0.32	868.04
SETα.9	3.13	0.31	917.19
SMA	3.30	0.68	736.67
WMAS1	3.31	0.62	729.58
ETMA	3.31	0.92	889.52
WMAS2	3.34	0.59	767.37
NAV	4.50	0.36	1314.33
DMA	5.78	-1.57	2146.32
DESα.2	5.87	2.47	2922.45
DESα.3	8.69	3.62	3928.83
DESα.4	11.49	4.64	4809.78
PF	11.93	-0.25	8530.98
DESα.5	14.32	5.55	5623.88
DESα.6	17.17	6.32	6405.30
DESα.7	20.06	6.98	7181.43
DESα.8	22.99	7.57	7981.43
DESα.9	25.99	8.09	8846.34

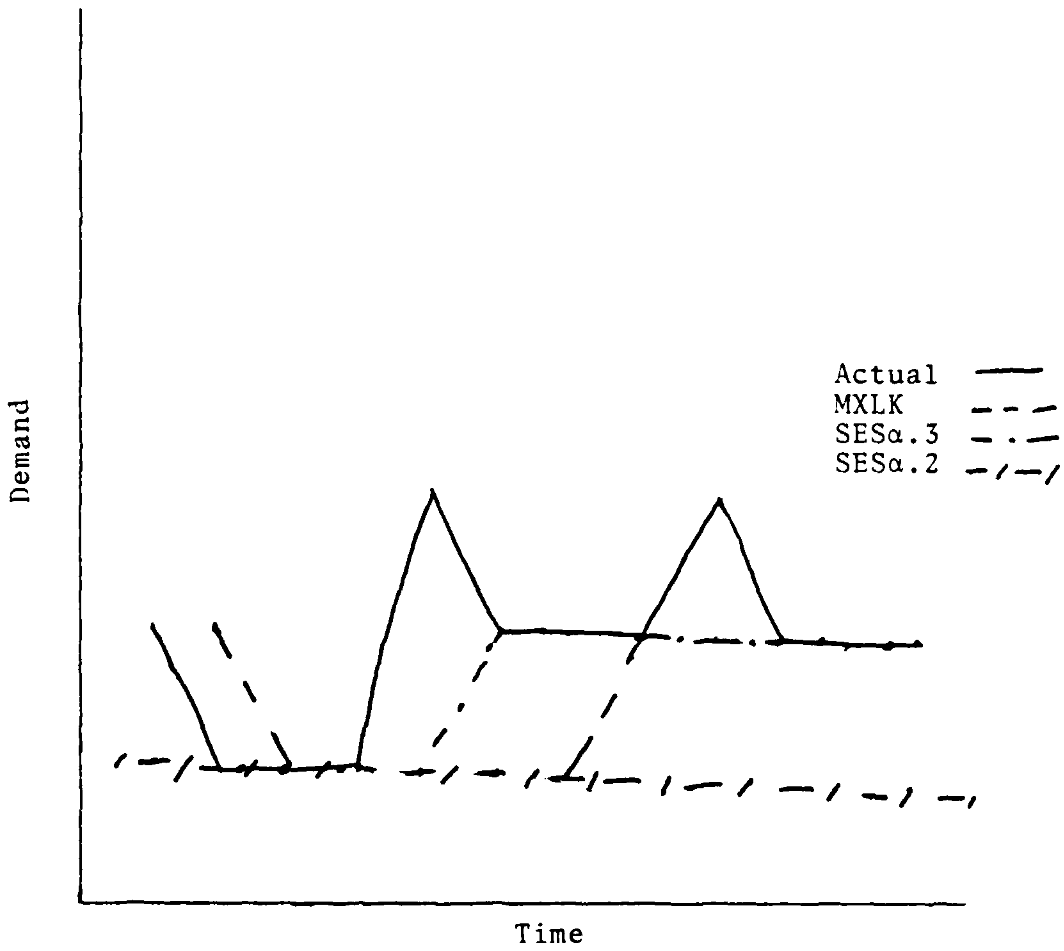

Figure 8

NSO Demand Pattern

TABLE 9

Statistics Summary

Model	MAD	MFE	VAR
SESα.2	2.80	2.47	851.56
MXLK	2.81	0.99	808.22
SESα.3	2.82	0.85	778.70

SESα.3. For NSO items, it was 14.32 compared with 2.82.

In Figure 9, DESC's model was compared against the actual aggregated demand of the replenishment items. It showed the same tendency as the graphed models in Figures 5 and 6. Namely, after period 5 it compared favorably with the actual demand pattern and the other models. This result indicates that the initial value used in period 1 may be bad, and is what caused the high MAD value for the model. For NSO item demand, a quick check of Table 11 in Appendix C shows that the model forecasts a straight line item demand of two units. Thus, it is just as good as the models looked at in Figure 8.

Briefly, this chapter has analyzed the results obtained from the computer runs. A summary of the findings will be presented in the next chapter along with the limitations and recommendations of this study.

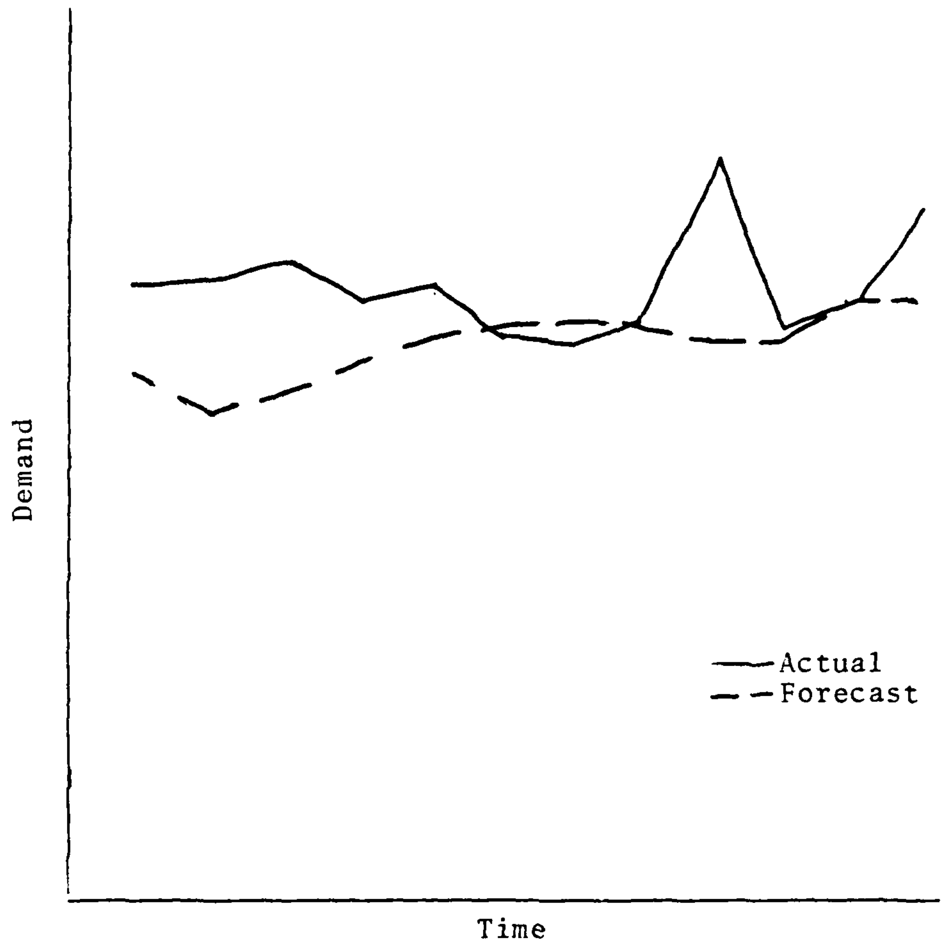

Figure 9

Double Exponential Smoothing

CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS

The research question addressed in this study was: Can a "better" model be found to replace the double exponential smoothing model currently used at DESC?

The results of this study indicate that a single exponential smoothing model with an α of 0.3 or a maximum likelihood model may be a better model than the current one in use at DESC. Both models have low MADs, 45.10 and 45.92, and MFEs, 7.45 and 2.84, in relation to the other models showing that they have the least amount of deviation from the actual demand experienced. This is especially true compared with the DESC model. Graph comparison of the models, though, showed that after an initialization period the DESC model followed the demand curve as well as the aforementioned models. Overall, the MAD indicated that the double exponentials were the worst, with the exception of $\alpha = 0.1$.

Limitations

The omittance of migratory data from the data bases may have caused some models to look better than they normally would in such circumstances. This is especially true of models which perform best when demand is constant with some random fluctuations.

Another limitation in differentiating between the models was the lack of an adequate analysis of variance to see if there were significant differences between the models with the best MADs and the DESC model.

Lastly, the inclusion of the initialization period of the models into the forecast statistics may have inflated the MAD of some models. However, the initialization period is sometimes important in the determination of a model and is, therefore, taken into account.

Recommendations

The recommendations of this study are as follows:

1. Compute the forecast statistics for periods 5 and on; then compare against those obtained in this study. This will check the effect of the initialization period upon the forecast statistics.

2. Conduct an analysis of variance upon the results of this study to see if statistically significant differences exist.

3. Run the single exponential smoothing model with α of 0.3 against some migratory data and compare with the DESC model.

APPENDIX A

DATA RETRIEVAL PROGRAM

The program in this appendix transferred data onto the data tape used in this study.

```
C PROGRAM COMBINES SAMPLE TAPES
      DIMENSION ISN(3),JSN(3),KSN(3) ,IQTY(4),IFRQ(4),JQTY(4),JFRQ(4),
     1KQTY(4),KFRQ(4)
      IYR=1
      JYR=2
      KYR=3
      NI=0
      NJ=0
      NK=0
      N0=0
      N1=0
      N2=0
      NL=0
      JMATCH=0
      KMATCH=0
      KSN(1)=5800
      KNSNF=0
      MISFRE=0
      ITAPE=4
C  READ TAPE 1ST PERIOD
    1 NI=NI+1
      READ(1,END=70)   ISN,IFLDB,(IQTY(IK),IK=1,4),(IFRQ(IL),IL=1,4)
C   TEST STOP
      IF(NI.GT.100) GO TO 70
      INSNF=ISN(3)
      IF(ISN(1).LT. 5805)  GO TO 1
      IF(ISN(1).GT. 6625)  GO TO 70
      IF(ITAPE.EQ.1) GO TO 4
C  READ TAPE 2ND PERIOD
    2 NJ=NJ+1
      READ(2,END=70)   JSN,JFLDB,(JQTY(IK),IK=1,4),(JFRQ(IL),IL=1,4)
      JNSNF=JSN(3)
      IF(JSN(1).LT. 5805)  GO TO 2
      IF(JSN(1).GT. 6625)  GO TO 70
C  MATCH TAPE1 TO TAPE 2
    4 IF(ISN(1).GT.JSN(1)) GO TO 12
      IF(ISN(1).LT.JSN(1)) GO TO 11
      IF(INSNF.GT.JNSNF) GO TO 12
      IF(INSNF.LT.JNSNF) GO TO 11
      JMATCH=JMATCH+1
C  MATCH 1ST MATCH TO TAPE 3
   14 ITAPE=4
      IF(ISN(1).GT.KSN(1)) GO TO 15
      IF(ISN(1).LT.KSN(1)) GO TO 1
      IF(INSNF.GT.KNSNF) GO TO 15
      IF(INSNF.LT.KNSNF) GO TO 1
      KMATCH=KMATCH+1
      GO TO 16
```

```
   11 ITAPE=1
      GO TO 1
   12 ITAPE=2
      GO TO 2
   15 ITAPE=3
C   TEST USING TAPE 2 RECORD AS TAPE 3...
    3 NK=NK+1
      DO 40 IK=1,4
      KQTY(IK)=JQTY(IK)
      KFRQ(IK)=JFRQ(IK)
      IF(IK.GT.3)  GO TO 40
      KSN(IK)=JSN(IK)
   40 CONTINUE
      KNSNF=KSN(3)
C   TEST STOP
      IF(NK.GT.100) GO TO 70
      GO TO 14
   16 ITAPE=4
C  CHECK ON ZERO DEMAND, TOTAL DEM
      NQTY=0
      DO 18 ID=1,4
   18 NQTY=NQTY(ID)+JQTY(ID)+KQTY(ID)
C    DUMP 0 DEM ITEMS
      IF(NQTY.LE.0)  NO=NO+1
      IF(NQTY.LE.0)  GO TO 1
C   CONVERT FLDB TO READABLE ICC ONLY
      M=1
      MASK=48
      CALL NC(MASK,IFLDB)
C  TEST IICC(0=P,16=B,32=2,48=1)
      IF(MASK.EQ.48)   GO TO 20
      IF(MASK.EQ.0)    GO TO 20
      IF(MASK.EQ.16)   GO TO 30
      IF(MASK.EQ.32)   GO TO 30
C  MISS FIRE ON ICC
      MISFRE=MISFRE+1
      WRITE(6,500) MASK,MISFRE
      GO TO 1
C  REPL ITEMS WRITTEN OUT
   20 NI=NI+1
   21 WRITE(6,501) M,  ISN,IYR  ,(IQTY(IK),IK=1,4),(IFRQ(IL),IL=1,4)
      WRITE(6,501) M,  JSN, JYR, (JQTY(IK),IK=1,4),(JFRQ(IL),IL=1,4)
      WRITE(6,501)  M, KSN,KYR  ,(KQTY(IK),IK=1,4),(KFRQ(IL),IL=1,4)
      GO TO 1
C   NSO ITEMS WRITTEN OUT
   30 M=2
      N2=N2+1
      GO TO 21
   70 CONTINUE
      WRITE(6,500)  NI,NJ,NK,NL,JMATCH,KMATCH,MISFRE ,NO,NI,N2
  500 FORMAT(10X,10I10)
  501 FORMAT(2X,13I8)
      STOP
      END
```

APPENDIX B

FORTRAN FORECASTING PROGRAM

The program in this appendix forecasts demand using each of the methods discussed in Chapter 2. It also computes the Mean Absolute Deviation, Mean Forecast Error, and the Variance.

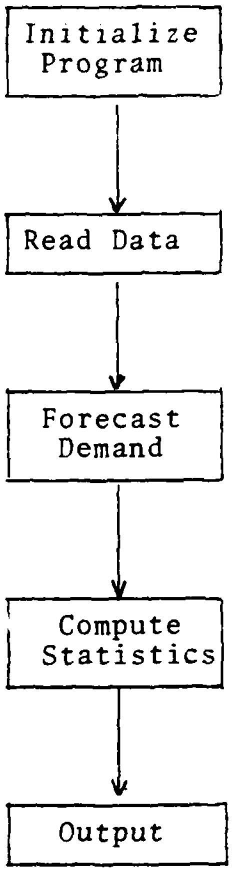

Figure 10

Computer Program Flow

```
C PROGRAM FORECASTS DEMAND
      INTEGER NAV,MXLK,WSMAG,WSMAT,SMA(8),DMA,POLY,ETMA,SX,DX,ST(12)
      INTEGER D(12),A,B,ISN(3),JSN(3),KSN(3),IQTY(4)
      INTEGER JQTY(4),KQTY(4),IFRQ(4),JFRQ(4),KFRQ(4),T,SUM(12)
      REAL AR(3),AD(3),FE(3)
      REAL ALPHA,BETA,MAD(35),VAR(35),MFE(35)
      BETA = 0.5
      DO 3 J=1,35
      MAD(J) = 0
      MFE(J) = 0
      VAR(J) = 0
    3 CONTINUE
      NI = 0
      DO 4 K=1,3
      AD(K) = 0
      AR(K) = 0
      FE(K) = 0
    4 CONTINUE
      DO 5 I=1,12
      SUM(I) = 0
    5 CONTINUE
C READ DATA
    1 NI = NI + 1
      READ(1,END=40) ISN,IYR,(IQTY(IK),IK=1,4),(IFRQ(IL),IL=1,4)
      READ(1,END=40) JSN,JYR,(JQTY(IK),IK=1,4),(JFRQ(IL),IL=1,4)
      READ(1,END=40) KSN,KYR,(KQTY(IK),IK=1,4),(KFRQ(IL),IL=1,4)
C TRANSFORM DATA QTY TO D FOR COMPUTE USE
      D(1) = IQTY(4)
      D(2) = IQTY(3)
      D(3) = IQTY(2)
      D(4) = IQTY(1)
      D(5) = JQTY(4)
      D(6) = JQTY(3)
      D(7) = JQTY(2)
      D(8) = JQTY(1)
      D(9) = KQTY(4)
      D(10) = KQTY(3)
      D(11) = KQTY(2)
      D(12) = KQTY(1)
C NAIVE MODEL, NAV
      I=1
      J=1
    2 NAV = D(I)
      X = D(I+1) - NAV
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      I=I+1
```

```
      IF(I.LT.12) GO TO 2
      MAD(J) = (AD(1)/11) + MAD(J)
      VAR(J) = (AR(1)/11) + VAR(J)
      MFE(J) = (FE(1)/11) + MFE(J)
C MAXIMUM LIKLIHOOD MODEL, MXLK
      I=1
      J=J+1
      AD(1)=0
      AR(1)=0
      FE(1)=0
      MXLK = D(1)
    6 X = D(I+1) - MXLK
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      I=I+1
      IF(I.EQ.12) GO TO 8
      MXLK = (D(I) + (I-1)*MXLK)/I
      GO TO 6
    8 MAD(J) = (AD(1)/11) + MAD(J)
      VAR(J) = (AR(1)/11) + VAR(J)
      MFE(J) = (FE(1)/11) + MFE(J)
C POLYNOMIAL FITTING MODEL, POLY
      I=4
      J=J+1
      AD(1)=0
      AR(1)=0
      FE(1)=0
   10 POLY = 3*D(I-1) - 3*D(I-2) + D(I-3)
      X = D(I) - POLY
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      I=I+1
      IF(I.LT.13) GO TO 10
      MAD(J) = (AD(1)/9) + MAD(J)
      VAR(J) = (AR(1)/9) + VAR(J)
      MFE(J) = (FE(1)/9) + MFE(J)
C WEIGHTED MOVING AVERAGE SET 1, WSMAD
      I=5
      J=J+1
      AD(1)=0
      AR(1)=0
      FE(1)=0
   14 WSMAD = (4*D(I-1) + 3*D(I-2) + 2*D(I-3) + D(I-4))/10
      X = D(I) - WSMAD
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
```

```
      FE(1) = X + FE(1)
      I=I+1
      IF(I.LT.13) GO TO 14
      MAD(J) = (AD(1)/8) + MAD(J)
      VAR(J) = (AR(1)/8) + VAR(J)
      MFE(J) = (FE(1)/8) + MFE(J)
C WEIGHTED MOVING AVERAGE SET 2, WSMAT
      I=5
      J=J+1
      AD(1)=0
      AR(1)=0
      FE(1)=0
   18 WSMAT = (4*D(I-1) + D(I-2) + D(I-3) + D(I-4))/7
      X = D(I) - WSMAT
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      I=I+1
      IF(I.LT.13) GO TO 18
      MAD(J) = (AD(1)/8) + MAD(J)
      VAR(J) = (AR(1)/8) + VAR(J)
      MFE(J) = (FE(1)/8) + MFE(J)
C SINGLE MOVING AVERAGE,SMA,AND DOUBLE MOVING AVERAGE,DMA
      I=5
      J=J+1
      KI=1
      AD(1)=0
      AR(1)=0
      FE(1)=0
   22 SMA(KI) = (D(I-1) + D(I-2) + D(I-3) + D(I-4))/4
      X = D(I) - SMA(KI)
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      IF(I.LT.9) GO TO 24
      DMA = (SMA(KI-1) + SMA(KI-2) + SMA(KI-3) + SMA(KI-4))/4
      A = (2*SMA(KI)) - DMA
      B = (2*SMA(KI))/3
      DMA = A + B
      X = D(I) - DMA
      AD(2) = ABS(X) + AD(2)
      AR(2) = X**2 + AR(2)
      FE(2) = X + FE(2)
   24 I=I+1
      KI=KI+1
      IF(I.LT.13) GO TO 22
      MAD(J) = (AD(1)/8) + MAD(J)
      VAR(J) = (AR(1)/8) + VAR(J)
```

```
      MFE(J) = (FE(1)/8) + MFE(J)
      J=J+1
      MAD(J) = (AD(2)/4) + MAD(J)
      VAR(J) = (AR(2)/4) + VAR(J)
      MFE(J) = (FE(2)/4) + MFE(J)
C EXPONENTIAL SMOOTHING; SINGLE,SX; SINGLE TREND ST; DOUBLE DX
      ALPHA = 0.1
   25 I=2
      SX = 0.75*D(I-1)
      DX = 0.85*D(I-1)
      ST(I-1) = 0.75*D(I-1)
      DO 60 K=1,2
      AR(K) = 0
      AD(K) = 0
      FE(K) = 0
   60 CONTINUE
      T=0
   26 SX = (ALPHA*(D(I-1) - SX)) + SX
      X = D(I) - SX
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      ST(I) = (ALPHA*D(I-1)) + ((1-ALPHA)*(ST(I-1)+T))
      T = BETA*(ST(I)-ST(I-1)) + ((1-BETA)*T)
      X = D(I) - ST(I)
      AD(2) = ABS(X) + AD(2)
      AR(2) = X**2 + AR(2)
      FE(2) = X + FE(2)
      DX = (ALPHA*(SX-DX)) + DX
      X = D(I) - DX
      AD(3) = ABS(X) + AD(3)
      AR(3) = X**2 + AR(3)
      FE(3) = X + FE(3)
      I=I+1
      IF(I.LT.13) GO TO 26
      J=J+1
      MAD(J) = (AD(1)/11) + MAD(J)
      VAR(J) = (AR(1)/11) + VAR(J)
      MFE(J) = (FE(1)/11) + MFE(J)
      J=J+1
      MAD(J) = (AD(2)/11) + MAD(J)
      VAR(J) = (AR(2)/11) + VAR(J)
      MFE(J) = (FE(2)/11) + MFE(J)
      J=J+1
      MAD(J) = (AD(3)/11) + MAD(J)
      VAR(J) = (AR(3)/11) + VAR(J)
      MFE(J) = (FE(3)/11) + MFE(J)
      ALPHA=ALPHA+0.1
```

```
      IF(ALPHA.GT.0.9) GO TO 27
         GC TC 25
   27 CONTINUE
C DO62 MODEL, ETMA
      I=9
      DO 65 K=1,3
      AR(K) = 0
      AD(K) = 0
      FE(K) = 0
   65 CONTINUE
      J=J+1
   28 ETMA = (D(I-1)+D(I-2)+D(I-3)+D(I-4)+D(I-5)+D(I-6)+D(I-7)+D(I-8))
      ETMA = (3*ETMA)/24
      X = D(I) - ETMA
      AD(1) = ABS(X) + AD(1)
      AR(1) = X**2 + AR(1)
      FE(1) = X + FE(1)
      I=I+1
      IF(I.LT.13) GO TO 28
      MAD(J) = (AD(1)/4) + MAD(J)
      VAR(J) = (AR(1)/4) + VAR(J)
      MFE(J) = (FE(1)/4) + MFE(J)
C ALL MODELS HAVE RUN
      SUM(1) = D(1) + SUM(1)
      SUM(2) = D(2) + SUM(2)
      SUM(3) = D(3) + SUM(3)
      SUM(4) = D(4) + SUM(4)
      SUM(5) = D(5) + SUM(5)
      SUM(6) = D(6) + SUM(6)
      SUM(7) = D(7) + SUM(7)
      SUM(8) = D(8) + SUM(8)
      SUM(9) = D(9) + SUM(9)
      SUM(10) = D(10) + SUM(10)
      SUM(11) = D(11) + SUM(11)
      SUM(12) = D(12) + SUM(12)
      GC TC 1
C SUMMARY STATISTICS PRINTOUT
   40 CONTINUE
      XN = NI - 1
      DO 50 J=1,35
      MAD(J) = MAD(J)/XN
      VAR(J) = VAR(J)/XN
      MFE(J) = MFE(J)/XN
   50 CONTINUE
      PRINT 69
      PRINT 698,NI
      PRINT 1C0
      PRINT 500,MAD
```

```
      PRINT 300
      PRINT 500,VAR
      PRINT 400
      PRINT 200,MFE
      PRINT 699
      PRINT 700,SUM
   69 FORMAT (1X,5HNI IS)
  100 FORMAT (1X,6HMAD IS)
  200 FORMAT (1X,10F10.2)
  300 FORMAT (1X,6HVAR IS)
  400 FORMAT (1X,6HMFE IS)
  500 FORMAT (1X,8F15.2)
  698 FORMAT (1X,I5)
  699 FORMAT (1X,6HSUM IS)
  700 FORMAT (1X,12I9)
      STOP
      END
```

APPENDIX C

DEMAND DATA FORECASTS

Actual and forecasted demand data are contained in this appendix for aggregate replenishment items and NSO items.

TABLE 10

Average Aggregate Replenishment Item Demand Forecast

Model	Quarter 1	2	3	4	5	6	7	8	9	10	11	12
ACTUAL	87	89	91	86	88	82	81	84	108	84	88	101
NAV	--	87	89	91	86	88	82	81	84	108	84	88
MXLK	--	87	88	89	88	88	87	86	86	89	88	88
PF	--	--	--	94	74	97	68	85	91	153	12	120
WMAS1	--	--	--	--	88	88	86	83	83	93	91	91
WMAS2	--	--	--	--	87	88	84	82	83	97	87	89
SMA	--	--	--	--	88	88	86	84	83	88	89	91
DMA	--	--	--	--	--	--	--	--	86	85	85	86
SESα.1	65	67	69	71	72	73	74	74	75	78	78	79
SESα.2	65	69	73	76	77	79	79	79	80	85	84	84
SESα.3	65	71	76	80	81	82	81	80	81	89	87	87
SESα.4	65	73	79	83	83	84	82	81	82	92	88	87
SESα.5	65	75	82	86	87	86	83	81	82	94	88	87
SESα.6	65	77	84	88	86	86	83	81	82	98	89	88
SESα.7	65	79	84	88	86	87	83	81	83	100	88	87
SESα.8	65	81	87	90	87	88	83	81	83	102	87	87
SESα.9	65	83	88	90	86	87	82	81	83	105	85	87

TABLE 10, continued

Model	Quarter 1	2	3	4	5	6	7	8	9	10	11	12
SETα.1	65	67	70	74	78	82	85	88	91	95	97	100
SETα.2	65	69	75	81	86	90	92	93	112	120	120	117
SETα.3	65	71	78	85	90	94	93	91	89	94	92	91
SETα.4	65	73	79	86	89	91	89	86	85	93	92	91
SETα.5	65	75	82	88	89	89	86	84	84	96	93	91
SETα.6	65	77	84	90	89	89	85	82	82	97	92	90
SETα.7	65	79	86	90	88	88	84	81	82	100	91	89
SETα.8	65	81	87	90	87	87	83	81	83	103	90	88
SETα.9	65	83	88	91	87	88	83	81	83	106	87	87
DESα.1	74	73	72	71	71	71	71	71	71	71	72	73
DESα.2	74	72	71	71	72	73	74	75	76	77	78	79
DESα.3	74	71	71	72	74	76	77	78	78	78	81	83
DESα.4	74	70	71	74	77	79	81	81	81	81	85	86
DESα.5	74	69	72	77	81	83	84	83	82	82	88	88
DESα.6	74	68	73	79	84	85	85	83	81	81	91	89
DESα.7	74	67	75	81	85	85	86	83	81	82	94	89
DESα.8	74	66	78	85	89	87	87	83	81	82	97	88
DESα.9	74	65	81	87	89	85	86	82	81	83	103	87
ETMA	--	--	--	--	--	--	--	--	86	88	88	87

TABLE 11

Average NSO Item Demand Forecast

Model	Quarter 1	2	3	4	5	6	7	8	9	10	11	12
ACTUAL	2	1	1	1	3	2	2	2	3	2	2	2
NAV	-	2	1	1	1	3	2	2	2	3	2	2
MXLK	-	2	1	1	1	1	1	2	2	2	2	2
PF	-	-	-	2	1	9	0	3	2	5	0	3
WMAS1	-	-	-	-	1	4	2	2	2	2	2	2
WMAS2	-	-	-	-	1	2	2	2	2	2	2	2
SMA	-	-	-	-	1	1	2	2	2	2	2	2
DMA	-	-	-	-	-	-	-	-	1	2	2	2
SESα.1	1	1	1	1	1	1	1	1	1	1	1	1
SESα.2	1	1	1	1	1	1	1	1	1	1	1	1
SESα.3	1	1	1	1	1	2	2	2	2	2	2	2
SESα.4	1	1	1	1	1	2	2	2	2	2	2	2
SESα.5	1	1	1	1	1	2	2	2	2	3	3	3
SESα.6	1	2	1	1	1	2	2	2	2	3	3	3
SESα.7	1	2	1	1	1	3	3	3	2	2	2	2
SESα.8	1	2	1	1	1	2	2	2	2	3	1	2
SESα.9	1	2	1	1	1	3	2	2	2	3	2	2

TABLE 11, continued

Model	Quarter 1	2	3	4	5	6	7	8	9	10	11	12
SETα.1	1	1	1	1	1	1	1	1	2	2	2	2
SETα.2	1	1	1	1	1	2	2	2	2	3	3	3
SETα.3	1	1	1	1	1	2	2	2	2	2	2	2
SETα.4	1	1	1	1	1	2	2	2	2	3	3	3
SETα.5	1	2	2	1	1	2	2	2	2	3	3	3
SETα.6	1	2	1	1	1	2	2	2	2	3	2	2
SETα.7	1	2	1	1	1	2	2	2	2	3	2	2
SETα.8	1	2	1	1	1	3	2	2	2	3	2	2
SETα.9	1	2	1	1	1	3	2	2	2	3	2	2
DESα.1	2	2	2	2	2	2	2	2	2	2	2	2
DESα.2	2	2	2	2	2	2	2	2	2	2	2	2
DESα.3	2	2	2	2	2	2	2	2	2	2	2	2
DESα.4	2	2	2	2	2	2	2	2	2	2	2	2
DESα.5	2	2	2	2	2	2	2	2	2	2	2	2
DESα.6	2	1	1	1	1	1	2	2	2	2	3	3
DESα.7	2	1	1	1	1	1	3	3	3	2	2	2
DESα.8	2	1	2	1	1	1	2	2	2	2	3	2
DESα.9	2	1	2	0	1	1	3	3	3	3	3	2
ETMA	-	-	-	-	-	-	-	-	2	2	2	2

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